Nonsubsampled Contourlet Transformation Based Image Enhancement with Spatial and Statistical Feature Extraction for Classification of Digital Mammogram

K. Sankar, K.Nirmala

***Abstract-* In this paper, an efficient automated microcalcification classification system for breast cancer in mammograms using NonSubsampled Contourlet Transform (NSCT), Single Value Decomposition (SVD), Jacobi Moments and Support Vector Machine (SVM) is presented. The image is enhanced by using the preprocessing technique NonSubsampled Contourlet Transform (NSCT). The classification of microcalcification is achieved by extracting the features by using SVD and Jacobi moments and the outcomes are used as an input to the SVM classifier for classification.**

***Index Terms* – Mammography, breast cancer, texture features, NSCT, SVD, Jacobi moments and SVM.**

I. INTRODUCTION

Breast cancer is the second leading cause of cancer death in women. The world health organization's International Agency for Research on cancer (IARC) estimates that more than 400,000 women expire each year. Early detection of breast cancer is essential in reducing life losses. Mammography alone cannot prove that a suspicious area is malignant or benign. To decide that, the tissue has to be removed for examination using breast biopsy techniques. Diagnosis using mammograms is aimed at classifying the detected cancerous regions as benign or malignant.

Also retrospective studies have shown that in current breast cancer screening between 10% and 25% of the tumours are missed by the radiologist. Digital mammograms are among the most complicated medical images to be read due to their low contrast and the differences in the types of tissues. The aim of computer-aided diagnosis systems is to improve the opportunities of appropriate detection and evaluation of lesions . To do that, the first and critical step is to find a set of salient image features that can differentiate normal mammograms from abnormal ones.

In this paper the image is first enhanced by using the NSCT and then development of an automatic microcalcification classification is presented based on Jacobi moments feature and S feature.

II. RELATED WORK

Reports from the AMERICAN Cancer Society (ACS) shows that early diagnosed breast cancer patient can achieve survival rate as high as 97% before the spreading of the carcinoma cells [1].

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K. Sankar, Research scholar in Manonmaniam Sundaranar University, Tirunelveli, Tamil Nadu, India

Dr.K.Nirmala,Computer Science, Quaid-e-Millet College, Chennai Tamil Nadu, India

The enhancement of mammographic images could improve the visual effect of the mammogram, the most commonly used method is imposing enhancement preprocessing on the image [2].Wavelet Transform (WT), mathematical morphology etc. are the major commonly used image preprocessing technique [3-5].

Multiscale Geometric Analysis (MGA) is one of the research focuses on image enhancement [6]. MGA offers a high degree of directionality and anisotropy, so it gets widely used and developed. Up to now, many MGA methods have been proposed, such as Ridgelet[7], Curvelet[8], Bandelet[9], Contourlet[10] etc.

Various classification methodologies have been reported for the characterization of ROI such as, rule-based systems [11] and [12], fuzzy logic systems [16], statistical methods based on Markov random fields and support vector machines [13]. In addition some work reported in the literature employs neural network for cluster characterization and data mining technique for detection and classification of digital mammograms [14-16].

Moment based feature descriptors have evolved into a powerful tool for image analysis applications. Geometric moments present a low computational cost, but are highly sensitive to noise. Furthermore reconstruction is extremely difficult. Although not invariant under rotation, Hu's invariants [17] that are derived from geometric moments present invariance under linear transformations. Complex moments provide with additional invariant descriptors, but present the same problems regarding noise and reconstruction.

Global geometric moments and their invariants are widely used in many areas of image analysis, including pattern recognition [17], image reconstruction [18], and fingerprint Recognition [19]. In addition to geometric moments, which are also known as regular or ordinary moments, a number of other moments have been proposed. The notion of complex moments was introduced in [20] for deriving moment invariants. Teague suggested the use of orthogonal moments and introduced complex valued Zernike moments that are defined on a unit disk.

The main goal of this paper is enhance the mammogram image by using NSCT, the feature are extracted from the enhanced image by using Singular Value Decomposition (SVD) and Jacobi moments. The purpose of the system is to classify the images into normal and abnormal.

III. METHODS AND MATERIALS

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A. *Image Enhancement*

In this paper image is enhanced using NonsubSampled Contourlet Transform (NSCT).NSCT is shift invariant. From the NSCT coefficients the geometrical information is collected. The NSCT transforms the nonsubsampled pyramid, split the input into a lowpass subband and a highpass subband. Then a nonsubsampled DFB decomposes the highpass subband into several directional subbands. Repeated experimentation on lowpass subband reconstructs the image [21]. Finally the enhanced image is obtained with clarity and free from noise.

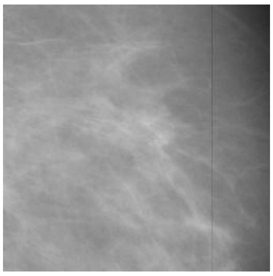

Fig.1.1(a) ROI Image (256x256)

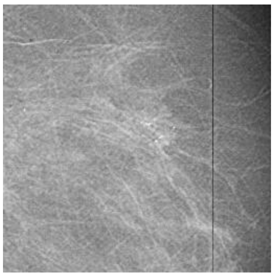

Fig.1.1(b)Enhanced Image(using NSCT 256x256)

B. *Feature Extraction*

Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. In the proposed method two features are combined for the classification of micro calcification in the mammogram. They are 'S' feature and the Jacobi moments.

C. *Jacobi Moments Extraction*

The Jacobi moments are calculated for the given ROI image. Jacobi moments for all overlapping window size of 4X4 are calculated [22]. Since the image has 256×256 sizes, it produces high number of Jacobi moments. The first 10 orders of moments are taken as the features. These features are selected by repeated experimentation. The algorithm is developed from [23].

D. *'S' Feature Extraction*

Two-dimensional discrete Haar wavelet transform is applied to the given ROI image. It decomposes an input image into four sub-bands, one average component (LL) and three detail components (LL, LH, HL, HH). Then SVD is applied to the LL sub band only. After applying SVD to the LL band of Wavelet Transform, three rectangular matrices S, U and V are obtained. S is a diagonal matrix which contains the square root Eigen values from U or V in descending order is selected and stored it separately in the feature set.

E. *Classification Phase*

In the proposed method SVM classifier is used to classify the images. There are two stages in the classification phase. In the first stage, the enhanced image is given as the input to classify mammograms into normal and abnormal. If it contains tumor (microcalcification), then the image is considered as the abnormal image. Finally, the abnormal mammogram is classified into malignant or benign in the second stage. SVM classifier is trained in each stage.

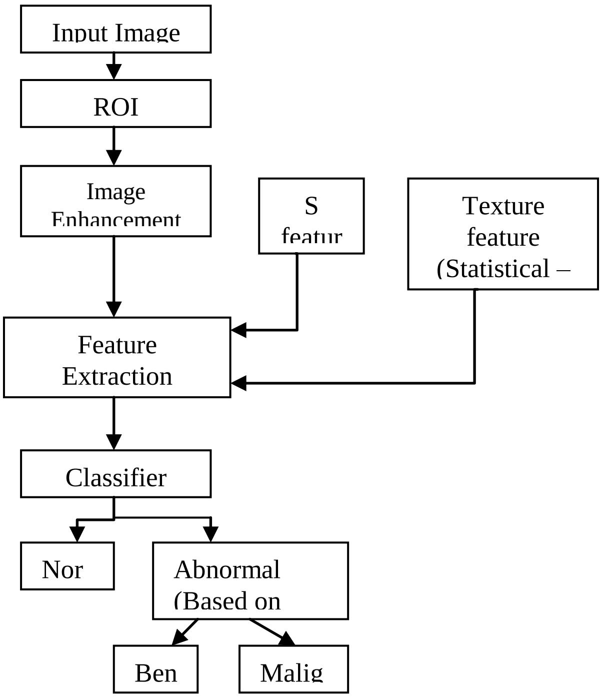

Fig. 3.1 Flowchart of the proposed method based on combined feature set with SVM

IV. PERFORMANCE MEASURE

The performance of the proposed approaches for the classification of benign and malignant patterns is measured by classification accuracy, sensitivity and specificity.

A. *Classification Accuracy*

It has been computed based on the number of correctly detected normal/abnormal images in order to evaluate the efficiency and robustness of the algorithm. The Metric is as follows:

$$Classification\ rate(\%)\ \frac{Total\ number of\ correctly\ classified\ images}{Total\ number of\ images} \quad (4.1)$$

V. EXPERIMENTAL RESULTS

MIAS database is employed for experiments. In MIAS database, there are 194 normal images and 25 microcalcification images available. All the images are considered for the classification test.

A. *Mammogram Classification System Based on Combined Feature Set*

In this section, the performance of the mammogram classification system based on combined feature set is explained. The number of training and testing images for the 1^{st} stage is given in Table 5.1.

Table 5.1 Number of Training and Testing samples for 1^{st} stage classifier

Type of image	No of training Images	No of Testing Images
Normal	120	74

Abnormal	15	10

The number of training and testing images for the 2nd stage is given in Table 5.2. The classification rate obtained using combined feature sets results are show in Table 5.3

Table 5.2 Number of Training and Testing samples for 2nd stage classifier

Type of image	No of training set	No of Testing set
Benign	7	5
Malignant	8	5

Table 5.3 Classification Result of the proposed system

Image Type	% Classification Rate
Normal	100
Abnormal	96.00
Benign	100
Malignant	87.5

VI. CONCLUSION

In this paper, an efficient method for enhancement and an automatic classification for classifying the digital mammogram has been proposed. Preliminary experiments are carried out in MIAS database. From the experimental results, it is observed that the proposed mammogram classification system based on combined feature set gives the better performance of 96% of classification rate and accuracy compare to other methods.

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